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Spatiotemporal shoreline dynamics of Namibian coastal lagoons derived by a dense remote sensing time series approach

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ABSTRACT

This paper proposes the remote sensing time series approach WLMO (Water-Land MOnitor) to monitor spatiotemporal shoreline changes. The approach uses a hierarchical classification system based on temporal MNDWI-trajectories with the goal to accommodate typical uncertainties in remote sensing shoreline extraction techniques such as existence of clouds and geometric mismatches between images. Applied to a dense Landsat time series between 1984 and 2014 for the two Namibian coastal lagoons at Walvis Bay and Sandwich Harbour the WLMO was able to identify detailed accretion and erosion progressions at the sand spits forming these lagoons. For both lagoons a northward expansion of the sand spits of up to 1000m was identified, which corresponds well with the prevailing northwards directed ocean current and wind processes that are responsible for the material transport along the shore. At Walvis Bay we could also show that in the 30 years of analysis the sand spit's width has decreased by more than a half from 750m in 1984 to 360m in 2014. This ongoing cross-shore erosion process is a severe risk for future sand spit breaching, which would expose parts of the lagoon and the city to the open ocean. One of the major advantages of WLMO is the opportunity to analyze detailed spatiotemporal shoreline changes. Thus, it could be shown that the observed long-term accretion and erosion processes underwent great variations over time and cannot a priori be assumed as linear processes. Such detailed spatiotemporal process patterns are a prerequisite to improve the understanding of the processes forming the Namibian shorelines. Moreover, the approach has also the potential to be used in other coastal areas, because the focus on MNDWI-trajectories allows the transfer to many multispectral satellite sensors (e.g. Sentinel-2, ASTER) available worldwide.

Keywords: coastal lagoons, spatiotemporal dynamics, remote sensing, time series, shoreline

1 INTRODUCTION

Globally, coastal areas are densely populated ecosystems of high ecological, economic, and social importance (Costanza et al., 1997; Martínez et al., 2007). Coastal lagoons in particular play an important role as productive ecosystems, species-rich habitats, and areas for storm protection and tourism (Anthony et al., 2009). Along Namibia's west coast, the lagoons are separated from the Atlantic Ocean by sand spits formed along the shore. Two prominent Namibian lagoons are Walvis Bay and Sandwich Harbour (Glassom and Branch, 1997; Lass and Mohrholz, 2005; Miller and Becker, 2008) (Fig. 1). The sand spits forming the two lagoons are highly dynamic and are known to have altered their shape in historical time (DMC and CSIR, 2010; Schoonees et al., 1998; e.g. Wilkinson et al., 1989). Aeolian processes and longshore or cross-shore drifts are the main causes of these sand spit variations (Hughes et al., 1992; Schoonees et

39 al., 1998). In the long run such processes can lead to a diminishing of the lagoons either by a sedimentation
40 of the lagoons or by a breaching of the sand spits that exposes the lagoons to the open ocean (Schoonees
41 et al., 1998). Since such changes endanger the important habitats as well as the shipping and the port at
42 Walvis Bay, a detailed knowledge about the spatiotemporal variations in the sand spits is of high
43 relevance. So far, only long-term changes are determined using historical maps and aerial photographs of
44 several years or decades apart (Elfrink et al., 2003; Schoonees et al., 1998; Wilkinson et al., 1989), and single
45 point-based measurement for a short period of month are conducted (Lass and Mohrholz, 2005).
46 However, to enable the analysis of the relationship between forcing processes and actual sediment
47 transports requires frequent assessments of the sand spits shoreline variations over longer periods.

48 Traditional ground-survey techniques for shoreline extraction (Natesan et al., 2013) and techniques using
49 airborne (i.e. platforms on planes and UAVs) data acquisitions of optical photographs (Cermakova et al.,
50 2016; Long et al., 2016), SAR-data (Bates et al., 2006), or LiDAR data (Stockdon et al., 2002) are accurate,
51 but time-consuming, labor and cost intensive, and don't allow past assessments due to missing data.
52 Detailed reconstruction of past shoreline variations requires the availability of frequent past image
53 acquisitions with sufficient spatial resolution. Satellite remote sensing images of high spatial resolution
54 (e.g. Quickbird, Worldview) used by Lee (2016) and Mann and Westphal (2014) are sufficient in spatial
55 resolution but lack temporal data frequency. Landsat images are globally freely available at 30m spatial
56 resolution with a 16 day repeat rate, which are considered as suitable for large scale shoreline changes at
57 a fairly high frequency. Thus, Landsat imagery was frequently used to investigate developments of oceanic
58 coasts in general (Ghosh et al., 2015; Li and Damen, 2010; Maiti and Bhattacharya, 2009; Wang et al., 2017)
59 and to map shoreline variations at coastal lagoons to analyze erosion and accretion processes (e.g. Ahmed
60 et al., 2009; El-Asmar and Hereher, 2011; Kuleli, 2010).

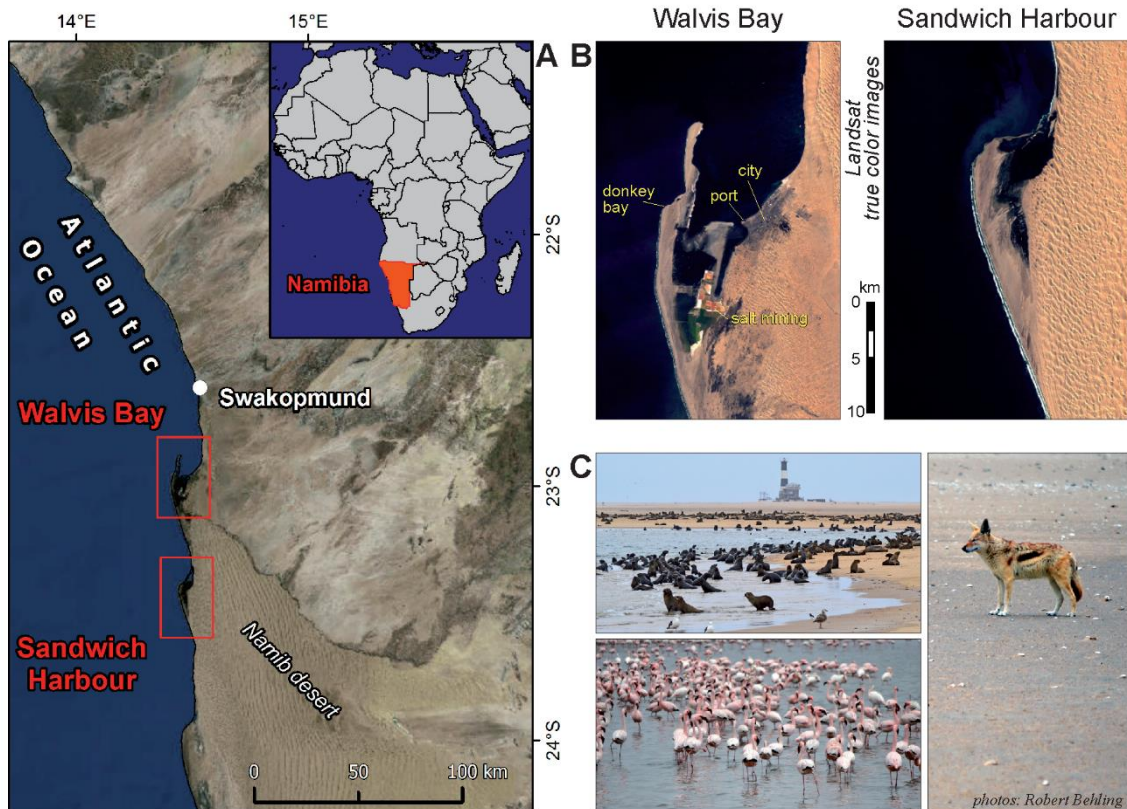
61 Regardless of the used satellite sensor, the assessment of shoreline changes is based on two major steps:
62 (i) shoreline detection in each dataset and (ii) shoreline change estimation between subsequent images.
63 The first step involves the binarization of images to distinguish between water and non-water pixels by
64 techniques such as image thresholding, classification, and segmentation. The second step includes the
65 change estimation along defined transects or the determination of overall changed areas based on the
66 binarized images or shoreline vectors extracted from these binary results. For both steps an overview of
67 techniques can be found in Aedla et al. (2015), Louati et al. (2015), and Wang et al. (2017). In general, the
68 determination of overall change underlies uncertainties that get introduced during both steps. The ability
69 and accuracy to extract the shoreline position in an image is influenced by the existence of clouds,
70 turbidity, fog, tidal areas, wet surfaces, and mixed pixels at the water-land front (Ryu et al., 2002).
71 Moreover, finding a threshold or classification rule that applies to all images of a time series is almost
72 impossible. The actual change estimate, the second step, is further influenced by geometric mismatches
73 or tidal variations between the compared images. All these uncertainties play a varying role in each image
74 and if using a large number of images they can lead to a large overestimation of the overall change rate
75 determination. In fact, the overall accuracy of such post-classification comparisons is generally considered
76 to be intrinsically low (Coppin et al., 2004), which is probably the main reason why shoreline change
77 studies so far used only few images of years or even decades apart even if more imagery would have been
78 available.

80 In this paper we propose a shoreline change rate determination technique, which uses the high temporal
81 information content of a dense Landsat time series with the goal to reduce the influence of uncertainty
82 effects in remote sensing image shoreline change rate determination. Therefore, we use a time series
83 change detection approach analyzing variations in the temporal domain and neglecting the shoreline
84 position extraction for each image. This approach was named Water-Land MOnitor (WLMO) and applied
85 for two of the most important Namibian lagoons at Walvis Bay and Sandwich Harbour to analyze how
86 long-term (e.g. longshore drifts and main wind direction) and short-term processes (e.g. storm events)
87 shape the sand spits at these lagoons and to evaluate potential hazards endangering the lagoons existence.

88 **2 STUDY SITES AND DATA**

89 **2.1 Study Sites**

90 The study sites Walvis Bay and Sandwich Harbour are located at the western Namibian coast, south of
91 Swakopmund (Fig. 1). The sand spits forming the coastal lagoons are several kilometers long and hundreds
92 of meters wide. Both lagoons are part of the Ramsar convention, which is an international treaty for the
93 conservation and sustainable use of internationally important wetlands (Ramsar, 2016). The Benguela
94 current causes an upwelling of nutrient-rich deep ocean water, which results in a high biological
95 production (DMC and CSIR, 2010). They are important habitats for large bird populations (e.g. flamingos
96 and pelicans), fish populations (e.g. steenbras, kabeljou) and mammals (e.g. seals). The study sites are
97 extremely dry with an annual rainfall of less than 20mm and due to the cold ocean water the area is subject
98 to frequent formation of fog (Hughes et al., 1992; Roux, 1974; Schoonees et al., 1998). The sand spits present
99 sandy and erodible land without any vegetation (Hughes et al., 1992) (Fig. 1c). Tides are semi-diurnal with
100 a mean tide range of 1.42 m and 0.62 m for spring tides and neap tides, respectively (DMC and CSIR, 2010;
101 Hughes et al., 1992). The prevailing winds are strong southwesterlies (Hughes et al., 1992; Roux, 1974). The
102 dominant wave direction is from south to south-westerly with a median significant wave height of 1.1 m
103 (Elfrink et al., 2003; Hughes et al., 1992; Schoonees et al., 1998). The sand spit of Walvis Bay protects a
104 town with the main deep water port of Namibia and a salt mining company in the direct vicinity (DMC
105 and CSIR, 2010; Elfrink et al., 2003; Schoonees et al., 1998). Sandwich Harbour was anchorage for whalers
106 for many decades in the 19th century but since then no substantial development took place and today it is
107 mainly used for occasional touristic activities (Wilkinson et al., 1989).

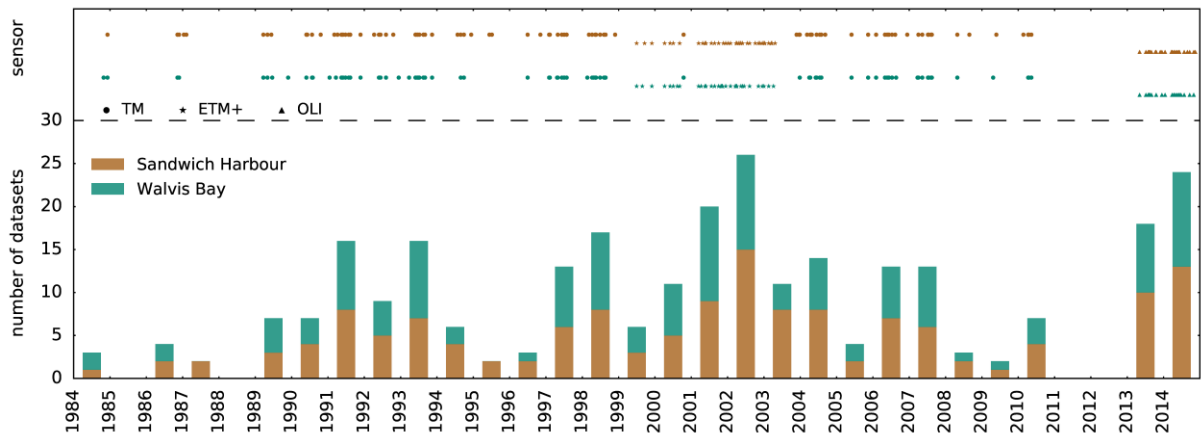


108

109 *Figure 1 Study sites: a) Location of the study sites, b) Landsat imagery showing the study sites of Walvis Bay and*
 110 *Sandwich Harbour. d) pictures of Walvis Bay mixed water-land landscape and rich fauna.*

111 **2.2 Data**

112 The remote sensing database comprises Landsat images of the sensors TM, ETM+, and OLI covering 30
 113 year period between 1984 and 2014. The images are retrieved from the USGS EarthExplorer
 114 (<http://earthexplorer.usgs.gov/>) as orthorectified Level 1T data. Both lagoons are located in the
 115 overlapping area between two Landsat WRS2 paths (path/row: 179/76 and 180/76), which allows for a
 116 higher temporal data repetition rate than usual. Images were selected on the basis that at least a part of a
 117 lagoon was cloud- and fog-free. In total, 130 images for Walvis Bay and 147 images for Sandwich Harbour
 118 were available (Fig. 2), representing an annual average of more than 4 images. At Sandwich Harbour data
 119 gaps exist in 1985, 1988, 2011, and 2012. At Walvis Bay, acquisitions in two more years (1987 and 1995) are
 120 missing. The selected images have varying coverage of clouds, fog, flooded tidal areas, white spume on
 121 waves, and milky water due to Sulphur eruptions (Supplements 1, 2), which all have the potential to
 122 hamper the discrimination between water and land.



123

124 *Figure 2 Database of partially cloud.- and fog-free Landsat images available at the study sites.*

125 **3 METHOD**

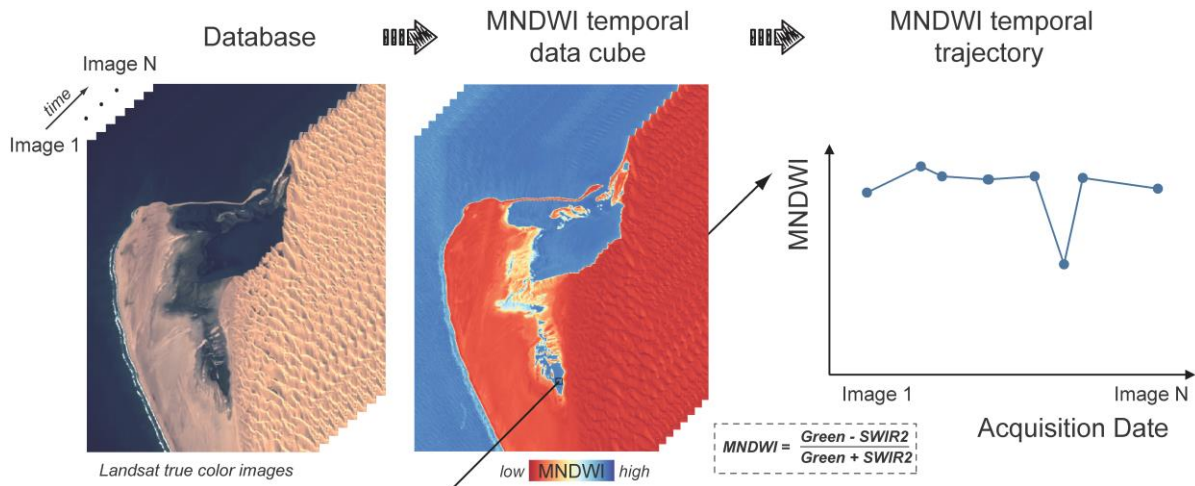
126 The WLMO (Water-Land MOnitor) is based on the analysis of temporal trajectories of the Modified
 127 Normalized Differenced Water Index (MNDWI) of Xu (2006). In the following the WLMO is described in
 128 terms of performed remote sensing data pre-processing (Sec 3.1), the developed MNDWI trajectory
 129 analysis method including its output parameters (Sec 3.2), and the validation procedure (Sec. 3.3)

130 **3.1 Pre-processing**

131 As a prerequisite for time series analysis the remote sensing images have to be comparable in their
 132 information content (Coppin et al., 2004). To meet the homogenization requirement, the Landsat images
 133 were converted from DN to Top of Atmosphere (TOA)-reflectance to adjust for radiometric scene
 134 variations caused by solar illumination differences, sensor specific gains and offsets, and differences in
 135 seasonality (Earth-Sun distance). Furthermore, relative image-to-image co-registration was performed to
 136 minimize artifact changes due to spatial misalignments. Therefore, the co-registration approach of Behling
 137 et al. (2014) was applied for each lagoon separately resulting in sub-pixel image-to-image alignment.

138 **3.2 Analysis of erosion and accretion processes using temporal MNDWI trajectories**

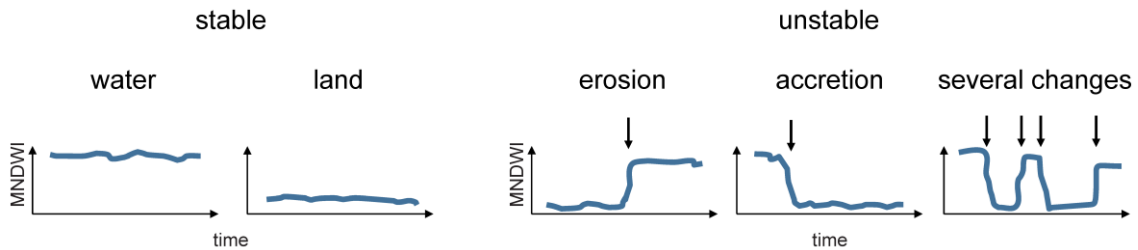
139 For each Landsat image the MNDWI of Xu (2006) was calculated and stacked to a MNDWI temporal data
 140 cube (Fig. 3). The MNDWI represents a ratio of the green and mid-infrared (MIR) spectral bands, utilizing
 141 the extreme low infrared reflectance of liquid water to discriminate between water and land bodies.



142

143 *Figure 3 Temporal MNDWI trajectories as basis for the WLMO approach*

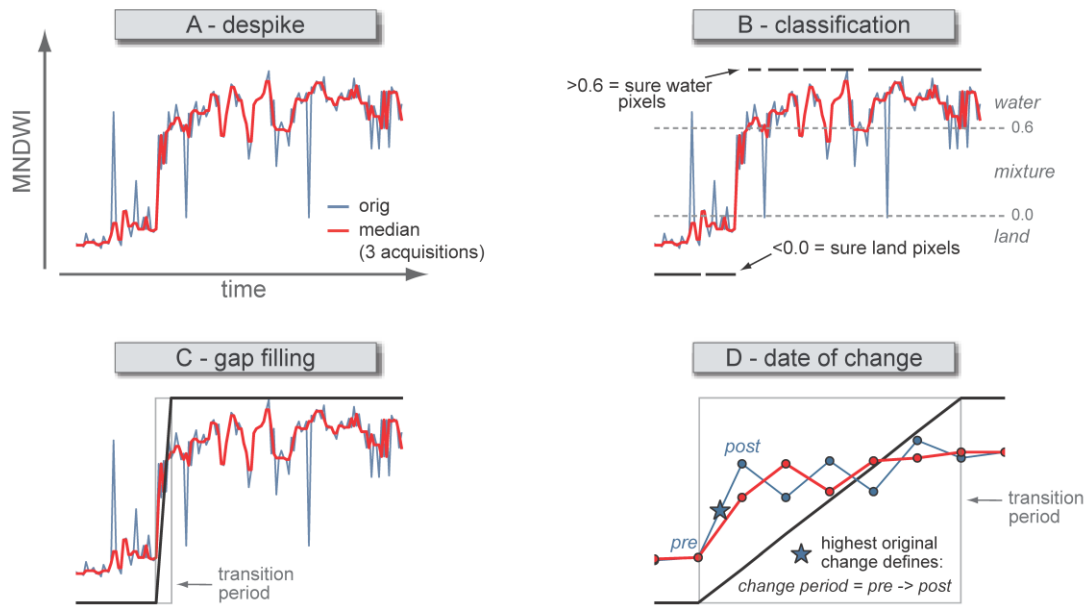
144 Each pixel of the MNDWI temporal data cube represents a temporal MNDWI trajectory (Fig. 3). Based on
 145 these temporal MNDWI trajectories the WLMO approach implements a hierarchical classification system
 146 (Fig. 4) for the detection of water-land transitions, which can be interpreted in terms of erosion and
 147 accretion processes. At top level, temporally stable and unstable areas are distinguished. The stable areas
 148 are subdivided into permanent water and permanent land. The unstable areas into single erosion, single
 149 accretion, or multiple land/water transitions.



150

151 *Figure 4 Concept for the detection and classification of changes based on temporal MNDWI trajectories. Arrows indicate*
 152 *the date of change in terms of erosion or accretion.*

153 The MNDWI trajectory-based classification of WLMO comprises four processing steps (Fig. 5). Step A:
 154 Smoothing of the MNDWI-trajectories using a temporal median filter (kernel size = 3) (Fig. 5a). This
 155 filtering removes outliers caused by cloud coverage, fog/haze, or temporally flooding. On the other hand
 156 it preserves longer-term variations such as erosion and accretion processes. Step B: Classification into sure
 157 pixels (water/land) and unsure pixels (mixture of both). Pixels are classified into sure open water
 158 (MNDWI>0.6) and sure land pixels (MNDWI<0.0) based on the median filtered MNDWI-trajectory (Fig.
 159 5b). The remaining non-classified pixels are interpreted as a mixed signal of water and land due to
 160 influences of haze, fog, moist surfaces, or sub-pixel mixtures at the shoreline between water and land.
 161 Thus, they either represent pixels with a disturbed signal or pixels during transition periods from land to
 162 water (erosion: t_e) or water to land (accretion: t_a). Step C: Gap filling between the sure pixels and
 163 identification of transition periods. The identification of transition periods relies on the temporal adjacent
 164 classes of sure water or sure land. If the sure classes match, the acquisitions in between are classified
 165 accordingly, and if not, a transition period is identified (Fig. 5c). Step D: Determination of the date of
 166 change during each transition period (Fig. 5d). The date of change during transition is associated with the
 167 period between subsequent images (pre- and post-image) of highest MNDWI change.



168

169 *Figure 5 Processing steps for pixel-based MNDWI trajectory analysis in WLMO.*

170 The result of the WLMO is a pixel-based binary temporal trajectory classifying each acquisition in water
 171 or land. Based on the binary trajectory the following parameters are provided:

- 172 • type of occurring transitions: erosion (t_e), accretion (t_a)
- 173 • date of transitions: period between subsequent images
- 174 • total number of transitions (t_{No}): $\Sigma t_{e/a}$
- 175 • overall stability:
 - 176 • stable pixels ($t_{No} == 0$). Further classified in permanent water or permanent land
 - 177 • unstable pixels ($t_{No} > 0$). Further characterized by change dominance: erosion ($\Sigma t_e > \Sigma t_a$),
 - 178 accretion ($\Sigma t_e < \Sigma t_a$), no dominance ($\Sigma t_e < \Sigma t_a$)

179 3.3 Validation procedure

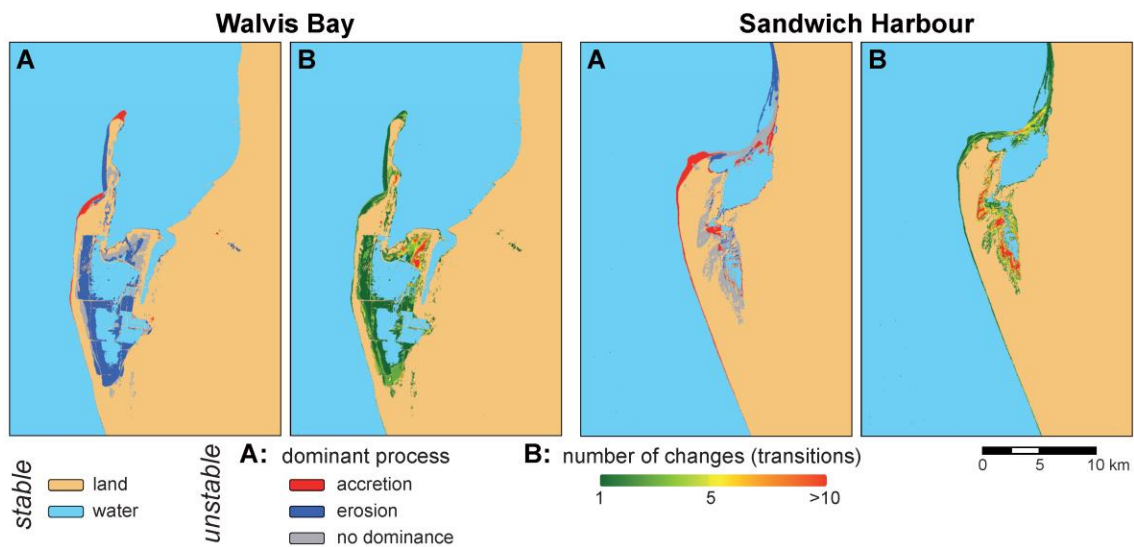
180 Due to the lack of existing reference data for past spatiotemporal progression of accretion and erosion
 181 processes at Walvis Bay and Sandwich Harbour, a detailed quantitative accuracy assessment is not
 182 possible. Therefore, we evaluated the quality of the obtained results by comparing the results of the
 183 change detection analysis with visual assessments of randomly selected available Landsat acquisitions and
 184 with published knowledge in the area. Moreover, we assessed how tide variations influence shoreline
 185 positions and evaluated how they influence the shoreline change determination results of WLMO.

186 4 RESULTS

187 The WLMO approach was applied to the Landsat time series for Walvis Bay and Sandwich Harbour. This
 188 section shows the achieved results in increasing detail. Section 4.1 presents the general output parameters
 189 of WLMO that differentiate the stability and dominant change processes (i.e. erosion or accretion).
 190 Section 4.2 provides annual spatiotemporal change rates of erosion and accretion for sub-regions of major
 191 changes. Section 4.3 shows the temporal development of the shoreline along two transects to demonstrate
 192 the temporal details that is achieved. Section 4.4 evaluates the quality of the derived WLMO results.

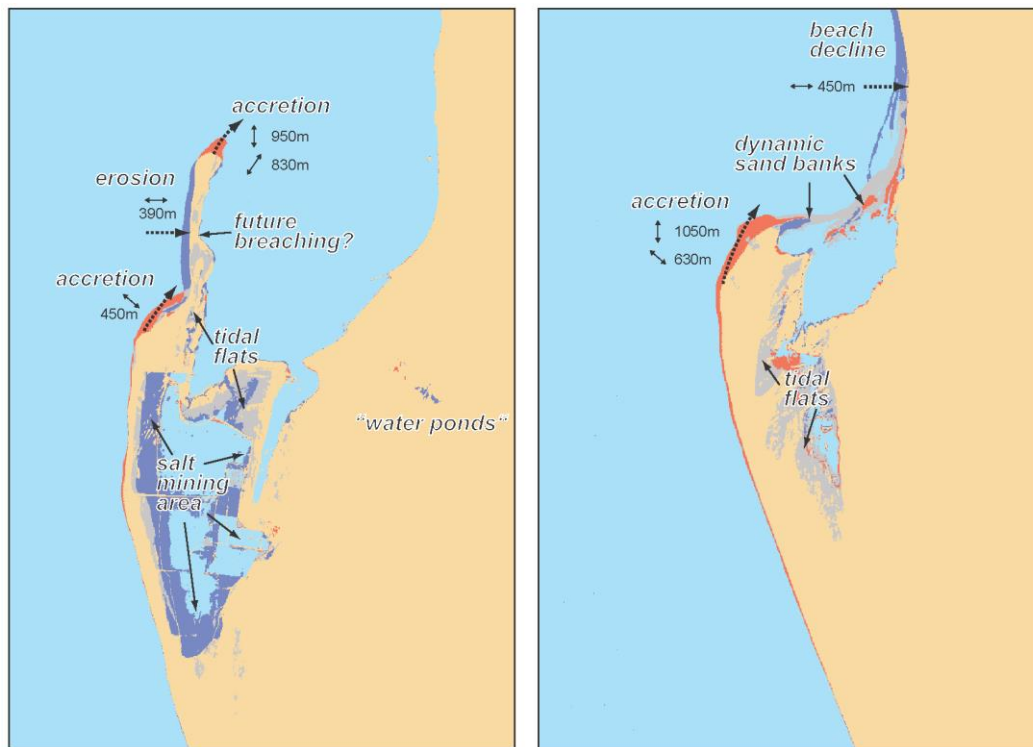
193 **4.1 Detection and mapping of erosion and accretion processes**

194 Fig. 6 depicts the WLMO results for both study sites, discriminating stable areas into water and land and
 195 characterizing unstable areas by change dominance and number of transitions. Unstable areas with a low
 196 number of transitions represent distinct accretion or erosion processes, whereas many transitions indicate
 197 that these areas are very variable over time. Distinct erosion or accretion processes are prevalent at the
 198 western flank of the sand spits, which are exposed to the open ocean. At Walvis Bay the tip and the
 199 shoulder (i.e. donkey bay) of the western flank accreted and the north-western flank eroded over the
 200 analyzed 30-year period. At Sandwich Harbour the whole western flank and tip of the sand spit was
 201 steadily growing, whereas steady long-term erosion processes are not identified. Overall, both sand spits
 202 expanded in northern direction. with up to 950m at Walvis Bay and 1050m at Sandwich Harbour (Fig. 7).



203

204 *Figure 6 Results for both coastal lagoons in terms of temporal stability (stable vs. unstable). Temporal unstable pixels*
 205 *are differentiated in terms of a) overall dominant change process and b) number of overall water-land*
 206 *transitions.*



207

208 *Figure 7 Interpretation of major change areas along with distances (number in meter) and directions (double headed*
 209 *arrows) of detected change. Left: Walvis Bay. Right: Sandwich Harbour (For color legend refer to Fig. 6A)*

210 In contrast to the western flanks, the eastern flanks of the sand spits are rather stable. In case of Walvis
 211 Bay, at the northern end of the sand spit, the combination of eroding western flank and stable eastern
 212 flank results in a decreasing width of the sand spit. At the thinnest location the sand spit has reduced its
 213 width by 390m from 750m in 1984 to 360m in 2014 (Fig. 7). This substantial erosion by more than a half of
 214 the sand spit's width clearly reveals the risk of future breaching, which would expose the city and the port
 215 of Walvis Bay to the open ocean.

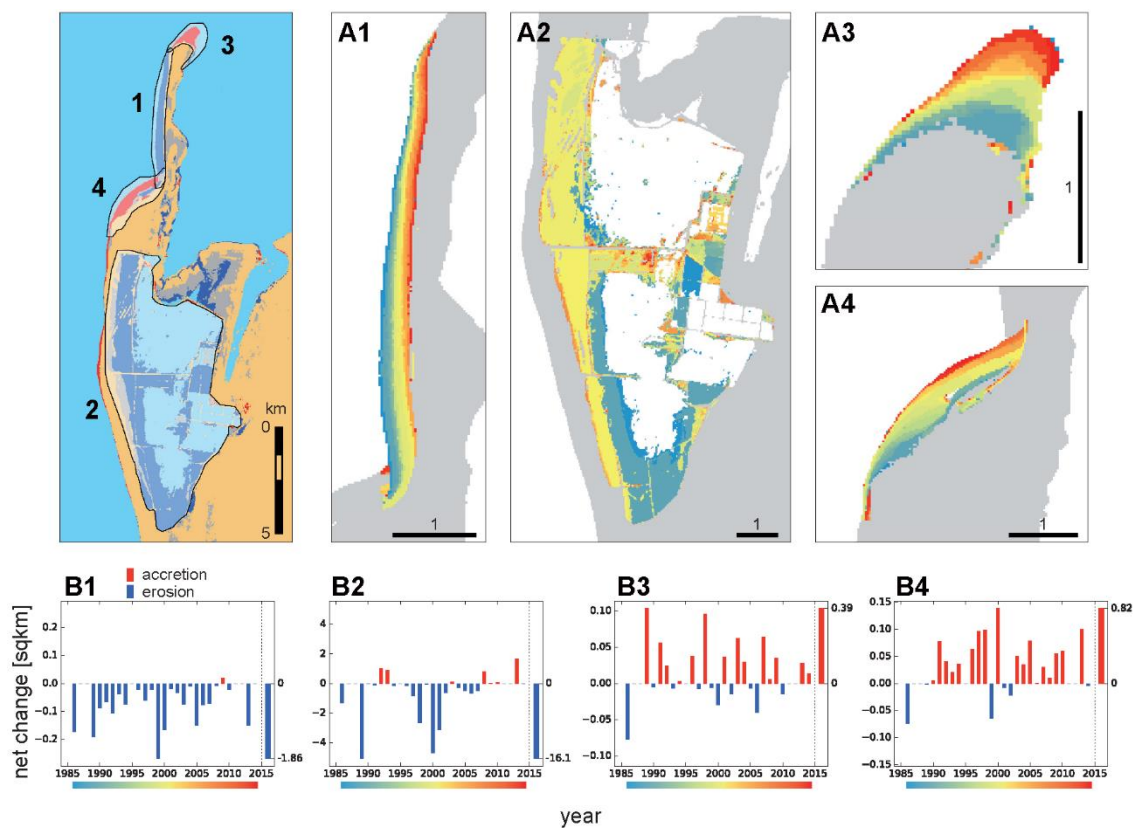
216 The regions that are protected by the sand spits experienced various change processes. The most obvious
 217 change is the large "eroding" area at Walvis Bay, which is caused by the expansion of the ponds of the salt
 218 mining company (DMC and CSIR, 2010). In contrast to these anthropogenic changes, further regions of
 219 frequent land/water transitions exist in both lagoons. These are naturally caused changes representing
 220 tidal flats, where the fluctuating tides cause temporary flooding and drying (Fig. 7).

221 At Sandwich Harbour two additional phenomena could be identified. Northeast of the main sand spit a
 222 variable development of small sand banks occurred. These sand banks grew from the sand spit in
 223 northeastern direction towards the mainland, but breached occasionally before they could totally cut off
 224 the lagoon from the open sea water (Supplement 2). The second phenomenon is the beach decline from
 225 west to east at the main coast in the northern part of the studied subset (Fig. 6, 7).

226 **4.2. Annual spatiotemporal change patterns for selected regions with dominant change regions**

227 For a deeper insight in the dynamics of the observed processes we analyzed the obtained results regarding
 228 annual spatiotemporal change patterns (Fig. 8, 9). In general the derived change patterns reveal that the
 229 dominating erosion or accretion processes were not a linear process but were rather characterized by great
 230 variations over time. For example, the northeastern progression of the tip of the Walvis Bay sand spit (Fig.

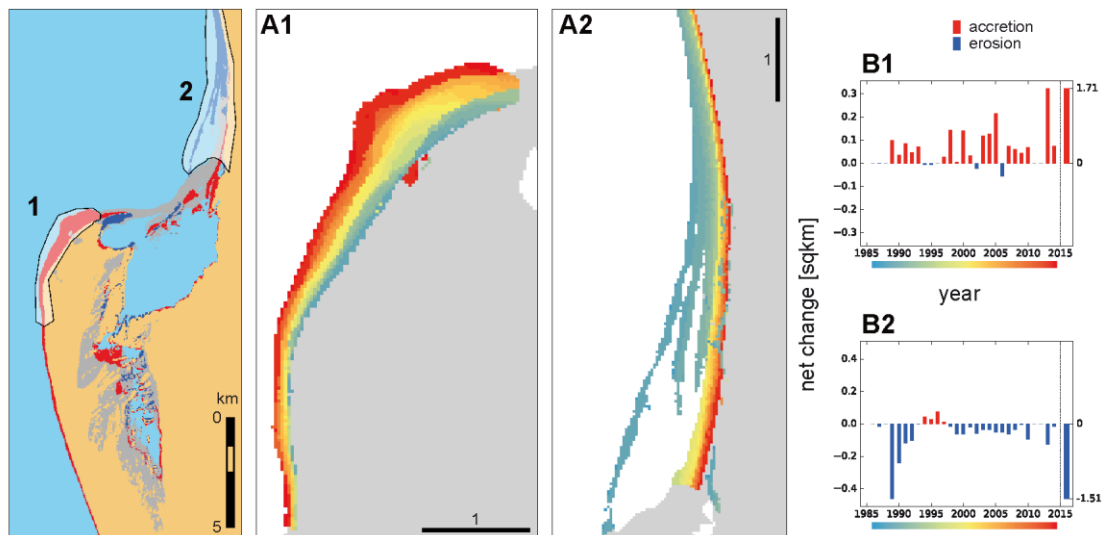
231 8A3) has resulted in a total expansion of 0.39km^2 over the last 30 years (Fig. 8B3), which represents a long-
 232 term average accretion rate of $13,000\text{m}^2/\text{a}$. However, this overall steady accretion varied greatly and
 233 underlay strong phases of accretion (up to $103,500\text{m}^2/\text{a}$ in 1989), but also phases of marginal accretion
 234 (e.g. $3600\text{m}^2/\text{a}$ in 1994), and even years with dominant erosion ($77,400\text{m}^2/\text{a}$ in 1986) (Fig. 8B3). Another
 235 example is the erosion at the western flank of the Walvis Bay sand spit (Fig. 8A1). In 30 years this eastern
 236 directed process eroded overall 1.86 km^2 of the western sand spit (Fig. 8B1), which is almost five times the
 237 0.39km^2 accretion at the tip. The long-term annual average of erosion is $62,000\text{m}^2$ and the annual erosion
 238 rate peaks in 1999 with $268,200\text{m}^2$ exceeding the long-term average by more than four times. The largest
 239 observed changes are caused by the expansion of sea water pre-evaporation ponds used for salt mining
 240 (Fig. 8A2). In 1989, 2000, and 2001 annual “erosion rates” of more than 3km^2 could be observed due to
 241 these pond expansions.



242

243 *Figure 8 Spatiotemporal change patterns at Walvis Bay. a) Spatiotemporal progression of either erosion or accretion*
 244 *processes (color represents the year the pixel was first eroded/accreted), b) annual net change rate of erosion*
 245 *and accretion pixels (each pixel covers 900m^2). Missing data in 1987, 1988, 1995, 2011, and 2012 (see Fig. 2). Four*
 246 *sub-regions are shown with either dominating erosion or accretion: 1 - Accretion at tip of sand spit, 2 - Erosion*
 247 *of the western flank, 3 - Accretion at donkey bay, 4 “Erosion” caused by salt mining.*

248 At Sandwich Harbour the findings reveal that the “beach decline” at the northeastern part occurred in two
 249 separate periods (Fig. 9A2, 9B2). At first a strong erosion took place around 1990, followed by a more
 250 stable period of low erosion and even accretion phases. The tip of the Sandwich Harbour expanded
 251 constantly in northern direction by a total of 1.71km^2 over the 30 years (Fig. 9A1, 9B1), which is more than
 252 four times the expansion observed at the tip at Walvis Bay (0.39km^2).



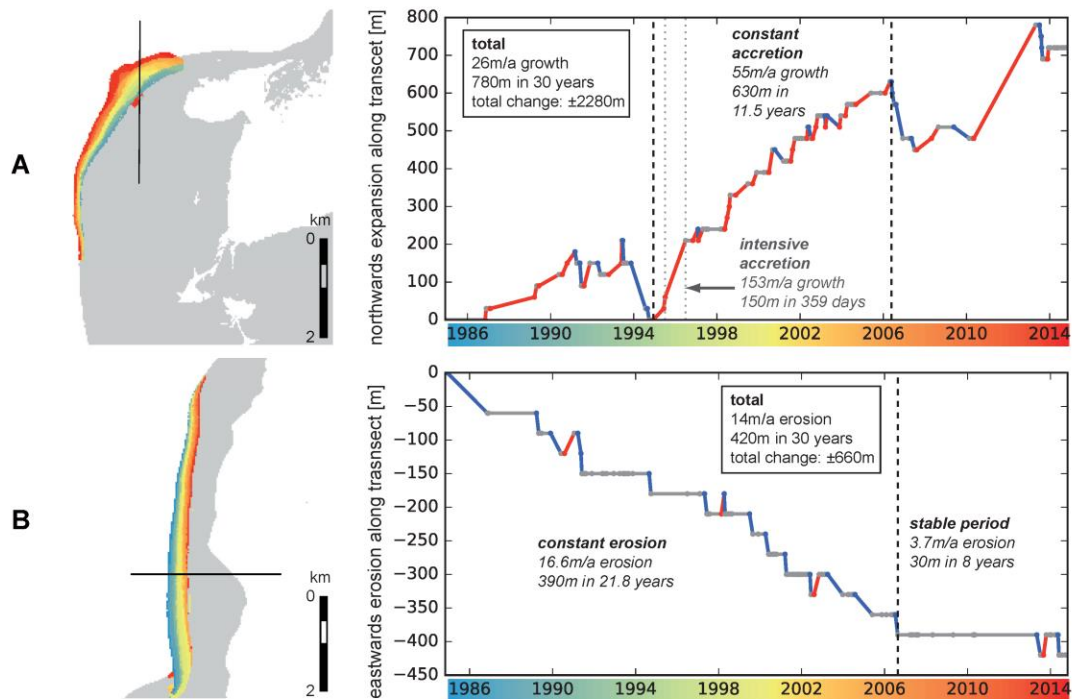
253

254 *Figure 9 Spatiotemporal change patterns at Sandwich Harbour. a) Spatiotemporal progression of either erosion or*
 255 *accretion processes (color represents the year the pixel was first eroded/accreted), b) annual net change rate of*
 256 *erosion and accretion pixels (each pixel covers 900m²). Missing data in 1988, 2011, and 2012 (see Fig. 2). Two*
 257 *sub-regions are shown of either dominating erosion or accretion: 1 Accretion at tip of sand spit. 2: Erosion of*
 258 *beaches NE of sand spit.*

259 4.3 Detailed erosion and accretion progression along transects

260 We analyzed the progression of erosion and accretion processes along transects (Fig. 10) in two selected
 261 areas of major change: (i) for the northern expansion of Sandwich Harbour and (ii) for the shrinkage of
 262 the western flank of the sand spit at Walvis Bay. This analysis allows to reveal detailed temporal variations
 263 of the longer-term progressing erosion and accretion processes. Along the transect at Walvis Bay (Fig.
 264 10B) the sand spit has receded 420m during the 30 year period, representing a long-term average rate of
 265 14m/a. Until 2007 the sand spit receded constantly with an annual rate of 16.6m followed by a stable
 266 period. This stability in recent years could also be observed for the complete southern part of the western
 267 flank, whereas the northern part has been subject to a higher erosion intensity during this period (Fig.
 268 10B, left panel).

269 At the tip of Sandwich Harbour (Fig. 10A) the intensity of accretion varies greatly over time. The first
 270 northwards expansion of ca. 150m until 1994 followed an intense and short phase of erosion back to the
 271 initial sand spit dimension of 1984. From that on the sand spit was growing constantly until 2006. In total,
 272 it expanded 630m in northern direction with a mean annual accretion rate of 55m/a. After a new erosion
 273 in 2006 the sand spit expanded to its final dimension in 2014 with a total growth of 780m along the
 274 transect. The total change of 2280m (i.e. sum of erosion and accretion) along the transect is approx. three
 275 times higher (292%) than the total accretion of 780m. At Walvis Bay the total change is only 157% (660m)
 276 of the total erosion of 420m. This difference in total change reveals a more irregular and variable process
 277 at the tip of Sandwich Harbour compared to the overall steady erosion of the Walvis Bay's western flank
 278 (Fig. 10B).



279

280 *Figure 10 Detailed change along transects for the dominant accretion at the sand spit tip at Sandwich Harbour (A) and*
 281 *the dominant erosion of the sand spit's western flank at Walvis Bay (B). Left: Transect location depicted on the*
 282 *subsets of Fig. 8A1 and 9A1. Right: Change along the transect. Y-Axis: Change in meter with 1984 as starting*
 283 *point 0; dots represent datasets of the Landsat time series; connectors between dots represent the occurred*
 284 *change between these datasets (blue: erosion, red: accretion, grey: stable).*

285 4.4 Validation

286 4.4.1 Qualitative Evaluation

287 The visual quality assessments of regions with dominating changes revealed that the WLMO approach
 288 detected the areas and the dates of changes correctly, which shows the robustness of the approach against
 289 temporary influencing factors such as clouds, fog, and small geometric shifts (see Supplements 1,2). In the
 290 highly variable tidal flats the approach occasionally has missed land/water transitions if the return period
 291 of sure water or sure land pixels was shorter than the median filter kernel of three temporal acquisitions
 292 (Fig. 5A) However, these rare misidentifications at the tidal flats have no influence for the evaluation of
 293 the spatiotemporal accretion and erosion processes at the sand spits of the coastal lagoons. According to
 294 Walvis Bay Salt Holdings (2017) and DMC and CSIR (2010) the approach has successfully identified the
 295 main expansions of the salt mining pre-evaporation ponds in 1988, 2000, and 2001 (Fig. 8).

296 The identification of the inland water ponds (Fig. 7), unknown to the authors before, proofed the
 297 objectivity of the approach to detect land/water transitions of any kind. The fact that almost no changes
 298 were identified at the stable coast of Walvis Bay and the stable eastern flanks of both sand spits (Fig. 7)
 299 confirms a very low susceptibility of the approach to identify false positives.

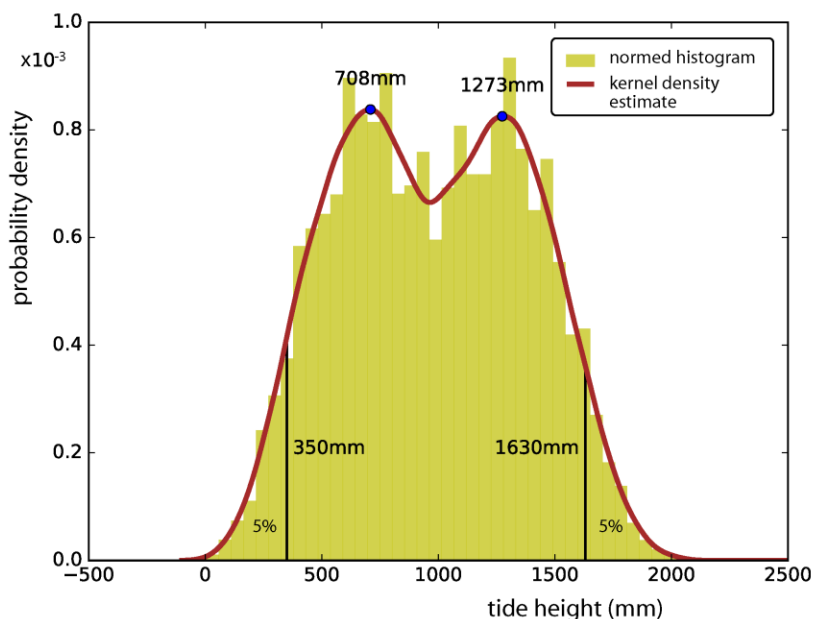
300 4.4.2 Influence of tides on the horizontal shoreline variations

301 For Walvis Bay basic bathymetry information can be found in DMC and CSIR (2010), Elfrink et al. (2003),
 302 Hughes et al. (1992), and Schoonees et al. (1998). The western flank, exposed to the open ocean, is much
 303 steeper than the eastern flank of the sand spit towards the protected lagoon and Walvis Bay city. For
 304 Donkey Bay (Fig. 1B), the most gentle part of the sand spits western flank (e.g. Elfrink et al., 2003, Fig. 1),

305 Schoones et al. (1998, Fig. 2) present an offshore slope of approximately 3.6° . At such a given slope of 3.6°
306 and 30m spatial resolution of a Landsat pixel, the tide range between two images needs to exceed 1.89m
307 to lead to an uncertainty in horizontal shoreline extraction of more than one Landsat pixel.

308 According to DMC and CSIR (2010) and Hughes et al. (1992) the tides at the two lagoons are semi-diurnal
309 with a mean tide range of 1.42m and 0.62m for spring tides and neap tides, respectively. Both, spring and
310 neap tides, fall below the 1 pixel uncertainty limit of 1.89m, meaning that the uncertainty of shoreline
311 extraction introduced by tide variations is within the sub-pixel range. Besides these two tide parameters
312 given in the literature, we analyzed the actual time series of tide data at Walvis Bay tide gauge. This gauge
313 is part of the Global Sea Level Observing System GLOSS (Caldwell et al., 2015) and tide data is available,
314 with some data gaps, since 1959 (UHSLC, 2018). Fig. 11 shows the tide height variations at Walvis Bay,
315 presenting a maximal tidal range (minimum and maximum of the whole time series) of approximately
316 2.1m and highest tide frequencies at 0.7m and 1.3m for low and high tides, respectively. Considering the
317 maximum tidal range of 2.1m by a given slope of 3.6° the horizontal uncertainty amounts to 33m,
318 representing an uncertainty of shoreline extractions of approx. one pixel if two subsequent Landsat images
319 would had been acquired at the two long-term tidal extremes. Ninety percent of all tide heights are within
320 a range of 1.3m (350mm-1630mm), resulting to 20m horizontal shoreline variations, which means subpixel
321 uncertainty in Landsat-based shoreline extraction. Overall, the horizontal uncertainty at Donkey Bay can
322 be expected to be less than one Landsat pixel.

323 Compared to Donkey Bay, the rest of the sand spits western flank at Walvis Bay is much steeper (e.g.
324 Elfrink et al., 2003, Fig. 1) and thus tide variations alter the horizontal shoreline position even less, which
325 means that tides can be neglected for the Landsat-based analysis in these regions. The fact that the more
326 gentle parts at the eastern flank (compared to Donkey Bay) are identified as stable (Figs. 6,7) shows further
327 the robustness of the WLMO approach, against tidal variations even if the horizontal shoreline
328 uncertainty might be higher than one pixel.



329

330 *Figure 11 – Tide height variation statistics at the Walvis Bay tide gauge since 1959.*

331 5 DISCUSSION

332 This paper proposed the WLMO (Water-Land-MOnitor), suited for the reconstruction of spatiotemporal
333 shoreline variations by utilizing dense Landsat time series data. It focusses on the robust change
334 assessment based on temporal MNDWI trajectories without the necessity to entirely map the shoreline
335 position in each image. Thus, the in other studies (e.g. Ghosh et al., 2015; Kuleli, 2010; Louati et al., 2015;
336 Wang et al., 2017) typically needed binarization of an image in water and non-water pixel for extracting
337 the shoreline position is not strictly needed. Instead the WLMO includes a third class representing unsure
338 pixels which are not sure water and sure land pixels. This allows the WLMO to detect changes only if the
339 sure classes are changing and not in uncertain cases (such as wet surfaces, fog, and mixed pixels at the
340 water-land front), in which other algorithms have to decide in each image if its water or not. That
341 robustness of the change algorithm allows the integration of many images and to densify the analyzed
342 data time series, making it possible to detect short-term changes in addition to the long-term change rates
343 between several years or even decades that are typical periods in studies using optical satellite remote
344 sensing data (e.g. Ghosh et al., 2015; Kuleli, 2010; Li and Damen, 2010; Wang et al., 2017). The implemented
345 median filtering to despise the MNDWI-trajectory makes the WLMO also robust against outliers such as
346 cloud coverage. However, by eliminating outliers it is always possible to eliminate real changes looking
347 alike. In case of the WLMO it means that if accretion and erosion happen during three subsequent images
348 the approach is not able to detect it. However, accretion processes are usually slow, which means that
349 such a cycle (water \leftrightarrow land) does usually not happen in quick succession. Thus, using a dense time series
350 minimizes the probability of missing such temporally variable accretion or erosion processes.

351 The results revealed that both sand spits at Walvis Bay and Sandwich Harbour expanded in northern
352 direction along the shore. In the 30-year period between 1984 and 2014 the approach identified the
353 maximum northern progression of the sand spit of 950 m (31.7m/a) at Walvis Bay and 1050m (35 m/a) at
354 Sandwich Harbour. These northern longshore expansions correspond with the prevailing south and
355 south-westerly wind, ocean current, and wave direction (see Section 2). This overall northern expansion
356 for Sandwich Harbour has already been described in the literature (Wilkinson et al., 1989), nevertheless,
357 it has never been quantified before. At Walvis Bay, Schoonees et al. (1998) and Hughes et al. (1992)
358 determined an annual progression rate of 17m/a over the 20th century by examining nautical maps and
359 aerial photographs. In comparison, our detected annual rate over the 30 year period of 1984-2014 of
360 31.7m/a is almost twice as high. Our finding correlates well with higher change rates for the more recent
361 times, such as found by Ward (1989) and Schoonees et al. (1998), who reported expansion rates of 26m/a
362 (1932 - 1989) and 22.6m/a (1980 - 1996), respectively. Another identified dominant change at Walvis Bay
363 is the eastern directed erosion at the western flank, which decreased the width of the northern sand spit
364 (Fig. 7). In Schoonees et al. (1998) this shrinkage was qualitatively discussed and the authors stressed the
365 risk of potential sand spit breaching. In our study we were able for the first time to quantify this erosion
366 with an annual rate of up to 14 m/a from 1984 to 2014 (Fig. 10B). The thinnest and thus probably the most
367 vulnerable part for breaching could be identified in the middle of the northern sand spit, where its width
368 has reduced from 750m to 360m with an rate of 13m/a (Fig. 7).

369 In contrast to previous studies at these lagoons the developed WLMO approach derives not only long-
370 term change rates but also spatially explicit change rates as well as their variations over time. For example,
371 it could be shown that the ocean-exposed sand spit at Walvis Bay is characterized by areas of dominant

372 erosion and accretion, whereas in Sandwich Harbour dominant erosion is missing. This difference exists
373 although both sand spits underlay mainly the same wind, wave, and ocean current processes (see Section
374 2). Thus, the absence of steady erosion at Sandwich Harbour might instead be explained by a higher
375 sediment supply from the nearby Namib (Holdt and Eckardt, 2017) or by a different shaped shelf with less
376 destructive wave energy at the shoreline. The argument of higher sediment supply is also supported by
377 the four times larger sand spit accretion at Sandwich Harbour compared to Walvis Bay (1.71km² vs.
378 0.39km²). Moreover, this paper clearly demonstrated that the erosion and accretion processes at both
379 lagoons greatly varied over time and thus cannot a priori be assumed as linear long-term processes. The
380 tips of the sand spits for example underwent long-term longshore progradations but also short-term
381 regressions (Fig. 8B3, 9B1, 10A) which are most likely caused by strong cross-shore wind and wave activity.
382 In contrast to the longshore accretion the erosion at the western flank of Walvis Bay was a more constant
383 process (Fig. 8B1, 10B), which implies no or negligible sediment transport in western direction.

384 The observed spatiotemporal sand spit dynamics also allow the evaluation of the risk of the lagoon's
385 habitats to get destroyed. Overall, both sand spits have a stable eastern shoreline (Fig. 7) that shows that
386 the lagoons are currently at a low risk to dry out because of silting. However, at Walvis Bay the ongoing
387 erosion of the western flank increases the risk of future sand spit breaching, which has the potential to
388 expose parts of the bay and the city to the open ocean. At Sandwich Harbour the frequent formation of
389 sand barriers show the constant risk that the lagoon will be cut off from the open sea water, which could
390 lead to a drying-out of the lagoon because of increased sedimentation. However, in the analyzed period
391 these sandbanks were always eroded before they could connect the sand spit and the main coast,
392 indicating a reduced risk after all.

393 **6 CONCLUSION**

394 This paper presents the WLMO (Water-Land MOnitor) approach for the mapping and monitoring of
395 spatiotemporal changes of coastal shorelines using remote sensing time series data. It is based on pixel-
396 oriented analysis of temporal MNDWI trajectories to distinguish efficiently between land and water and
397 to determine the period of their temporal variations, i.e. accretion (water to land) and erosion (land to
398 water). With four implemented steps, the temporal MNDWI-trajectory analysis is designed to
399 accommodate the uncertainties that arise in common mono-temporal shoreline extraction techniques
400 from the existence of clouds, turbidity, fog, tidal areas, wet surfaces, mixed pixels at the water-land front,
401 and geometric mismatches between compared images.

402 Applied to the two Namibians coastal lagoons Walvis Bay and Sandwich Harbour, the approach revealed
403 new qualitative and quantitative insights of the lagoon's spatiotemporal dynamics between 1984 and 2014
404 that go far beyond the long-term change rates that have been known before. It could be shown that long-
405 term erosion and accretion of the lagoon's sand spits are non-linear processes that underwent great
406 variations over time. Such variations were in detail demonstrated at the tips of the sand spits, which were
407 characterized by overall longshore accretion that were occasionally interrupted by short-term regressions
408 (erosion events) probably due to cross-shore wind and wave activity. The spatially explicit results of the
409 approach also allowed a quantitative comparison of the occurred changes at the two coastal lagoons. At
410 Sandwich Harbour the accretion at the sand spit was four times larger, indicating its higher supply of
411 sediments from the nearby Namib Desert. Moreover, we were able to identify the main risks that threaten

412 the habitats of the coastal lagoons. At Walvis Bay the ongoing eastern directed erosion reduced the width
413 of the sand spit significantly, and thus increased the risk of sand spit breaching which would expose a part
414 of the lagoon and city to the open ocean. At Sandwich Harbour the main risk could be found in the
415 frequent sand barrier formations at the mouth of the lagoon, which could result in the separation of the
416 lagoon from the open ocean and thus to an increased sedimentation.

417 The approach builds solely on the use of the MNDWI for the differentiation between water and land, and
418 could be directly transferred to other coastlines worldwide. This transfer might require adapting the
419 threshold for sure land classification to different natural conditions, especially if coastal areas are
420 vegetated and thus differ from the arid conditions of Namibian lagoons. Moreover, it can be extended to
421 other multispectral sensors to condense the analyzed time series and thus shorten the intervals between
422 which changes can be identified. Suitable data for such an extension would be the free of charge data of
423 the sensor systems Sentinel-2 (Drusch et al., 2012) and ASTER both comprising the required spectral bands
424 for the MNDWI used in this study.

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430 REFERENCES

- 431 Aedla, R., Dwarakish, G.S., Reddy, D.V., 2015. Automatic Shoreline Detection and Change Detection
432 Analysis of Netravati-Gurpur Rivermouth Using Histogram Equalization and Adaptive
433 Thresholding Techniques. *Aquat. Procedia*, (ICWRCOE'15) 4, 563–570.
434 <https://doi.org/10.1016/j.aqpro.2015.02.073>
- 435 Ahmed, M.H., El Leithy, B.M., Thompson, J.R., Flower, R.J., Ramdani, M., et al., 2009. Application of
436 remote sensing to site characterisation and environmental change analysis of North African
437 coastal lagoons. *Hydrobiologia* 622, 147–171. doi:10.1007/s10750-008-9682-8
- 438 Anthony, A., Atwood, J., August, P., Byron, C., Cobb, S., et al., 2009. Coastal Lagoons and Climate Change:
439 Ecological and Social Ramifications in US Atlantic and Gulf Coast Ecosystems. *Ecol. Soc.* 14, 8.
- 440 Bates, P.D., Wilson, M.D., Horritt, M.S., Mason, D.C., Holden, N., Currie, A., 2006. Reach scale floodplain
441 inundation dynamics observed using airborne synthetic aperture radar imagery: Data analysis and
442 modelling. *J. Hydrol.* 328, 306–318. <https://doi.org/10.1016/j.jhydrol.2005.12.028>
- 443 Behling, R., Roessner, S., Segl, K., Kleinschmit, B., Kaufmann, H., 2014. Robust Automated Image Co-
444 Registration of Optical Multi-Sensor Time Series Data: Database Generation for Multi-Temporal
445 Landslide Detection. *Remote Sens.* 6, 2572–2600. doi:10.3390/rs6032572
- 446 Cermakova, I., Komarkova, J., Sedlak, P., 2016. Using Uav to Detect Shoreline Changes: Case Study -
447 Pohranov Pond, Czech Republic, in: Halounova, L., Safar, V., Toth, C.K., Karas, J., Huadong, G.,
448 et al. (Eds.), *Xxiii Isprs Congress, I. Copernicus Gesellschaft Mbh, Gottingen*, pp. 803–808.
- 449 Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E., 2004. Digital change detection methods in
450 ecosystem monitoring: a review. *Int. J. Remote Sens.* 25, 1565–1596.
451 <https://doi.org/10.1080/0143116031000101675>
- 452 Costanza, R., D'Arge, R., De, G., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R.V.,
453 Paruelo, J., Raskin, R.G., Sutton, P., Van, D.B., 1997. The value of the world's ecosystem services
454 and natural capital. *Nature* 387, 253–260. <https://doi.org/10.1038/387253a0>
- 455 Caldwell, P. C., Merrifield, M. A., Thompson, P. R. 2015, Sea level measured by tide gauges from global
456 oceans — the Joint Archive for Sea Level holdings (NCEI Accession 0019568), Version 5.5, NOAA
457 National Centers for Environmental Information, Dataset, doi:10.7289/V5V4oS7W.

458 DMC, CSIR, 2010. Environmental impact assessment Study for Strategic Expansion of the Walvis Bay
459 Container Terminal. Final Environmental Impact Report and Environmental Management Plan.
460 (No. CSIR/CAS/EMS/ER/2009/0029/A).

461 Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., et al., 2012. Sentinel-2: ESA's Optical High-
462 Resolution Mission for GMES Operational Services. *Remote Sens. Environ.* 120, 25–36.
463 doi:10.1016/j.rse.2011.11.026

464 El-Asmar, H.M., Hereher, M.E., 2011. Change detection of the coastal zone east of the Nile Delta using
465 remote sensing. *Environ. Earth Sci.* 62, 769–777. doi:10.1007/s12665-010-0564-9

466 Elfrink, B., Prestedge, G., Rocha, C.B., Juhl, J., 2003. Shoreline evolution due to highly oblique incident
467 waves at Walvis Bay, Namibia. *Coast. Sediments* 3.

468 Ghosh, M.K., Kumar, L., Roy, C., 2015. Monitoring the coastline change of Hatiya Island in Bangladesh
469 using remote sensing techniques. *Isprs J. Photogramm. Remote Sens.* 101, 137–144.
470 doi:10.1016/j.isprsjprs.2014.12.009

471 Glassom, D., Branch, G., 1997. Impact of predation by greater flamingos *Phoenicopterus ruber* on the
472 macrofauna of two southern African lagoons. *Mar. Ecol. Prog. Ser.* 149, 1–12.
473 doi:10.3354/meps149001

474 Holdt, J.R. von, Eckardt, F.D., 2017. Dust activity and surface sediment characteristics of the dustiest river
475 in southern Africa: the Kuiseb River, Central Namib. *South Afr. Geogr. J.* 0, 1–18.
476 doi:10.1080/03736245.2017.1339627

477 Walvis Bay Salt Holdings, 2017. URL <http://www.wbsalt.co.za/company/> (accessed 7.7.17).

478 Hughes, P., Brundrit, G.B., Searson, S., 1992. The Vulnerability of Walvis Bay to Rising Sea Levels. *J. Coast.*
479 *Res.* 8.

480 Kuleli, T., 2010. Quantitative analysis of shoreline changes at the Mediterranean Coast in Turkey. *Environ.*
481 *Monit. Assess.* 167, 387–397. doi:10.1007/s10661-009-1057-8

482 Lass, H.U., Mohrholz, V., 2005. On the fluctuations and vertical structure of the shelf circulation off Walvis
483 Bay, Namibia. *Cont. Shelf Res.* 25, 1473–1497. doi:10.1016/j.csr.2005.04.012

484 Lee, I.-C., 2016. Instantaneous Shoreline Mapping from Worldview-2 Satellite Images by Using Shadow
485 Analysis and Spectrum Matching Techniques. *J. Mar. Sci. Technol.-Taiwan* 24, 1204–1216.
486 <https://doi.org/10.6119/JMST-016-1026-9>

487 Li, X., Damen, M.C.J., 2010. Coastline change detection with satellite remote sensing for environmental
488 management of the Pearl River Estuary, China. *J. Mar. Syst.* 82, S54–S61.
489 doi:10.1016/j.jmarsys.2010.02.005

490 Long, N., Millescamp, B., Guillot, B., Pouget, F., Bertin, X., 2016. Monitoring the Topography of a Dynamic
491 Tidal Inlet Using UAV Imagery. *Remote Sens.* 8, 387. <https://doi.org/10.3390/rs8050387>

492 Louati, M., Saidi, H., Zargouni, F., 2015. Shoreline change assessment using remote sensing and GIS
493 techniques: a case study of the Medjerda delta coast, Tunisia. *Arab. J. Geosci.* 8, 4239–4255.
494 doi:10.1007/s12517-014-1472-1

495 Maiti, S., Bhattacharya, A.K., 2009. Shoreline change analysis and its application to prediction: A remote
496 sensing and statistics based approach. *Mar. Geol.* 257, 11–23. doi:10.1016/j.margeo.2008.10.006

497 Mann, T., Westphal, H., 2014. Assessing Long-Term Changes in the Beach Width of Reef Islands Based on
498 Temporally Fragmented Remote Sensing Data. *Remote Sens.* 6, 6961–6987.
499 <https://doi.org/10.3390/rs6086961>

500 Martínez, M.L., Intralawan, A., Vázquez, G., Pérez-Maqueo, O., Sutton, P., Landgrave, R., 2007. The coasts
501 of our world: Ecological, economic and social importance. *Ecol. Econ., Ecological Economics of*
502 *Coastal Disasters* 63, 254–272. <https://doi.org/10.1016/j.ecolecon.2006.10.022>

503 Miller, R.M., Becker, T., 2008. The Geology of Namibia: Upper palaeozoic to cenozoic. Ministry of Mines
504 and Energy Geological Survey of Namibia.

505 Natesan, U., Thulasiraman, N., Deepthi, K., Kathiravan, K., 2013. Shoreline change analysis of Vedaranyam
506 coast, Tamil Nadu, India. *Environ. Monit. Assess.* 185, 5099–5109. <https://doi.org/10.1007/s10661-012-2928-y>

507

508 Ramsar, 2017. URL <http://www.ramsar.org/> (accessed 7.7.17).

509 Roux, P.J., 1974. Drift sand reclamation of Walvis Bay, South West Africa. *Int. J. Biometeorol.* 18, 121–127.
510 doi:10.1007/BF01452232

511 Ryu, J.H., Won, J.S., Min, K.D., 2002. Waterline extraction from Landsat TM data in a tidal flat - A case
512 study in Gomso Bay, Korea. *Remote Sens. Environ.* 83, 442–456. doi:10.1016/S0034-4257(02)00059-
513 7

514 Schoonees, J.S., Lenhoff, L., Raw, A.J., 1998. Preventing natural breaching of the major sand spit protecting
515 the port of Walvis Bay. *Coast. Eng. Proc.* 1.

- 516 Stockdon, H.F., Sallenger, A.H., List, J.H., Holman, R.A., 2002. Estimation of shoreline position and change
517 using airborne topographic lidar data. *J. Coast. Res.* 18, 502–513.
- 518 UHSLC Legacy Data Portal [WWW Document], URL <https://uhslc.soest.hawaii.edu/data/> (accessed
519 1.3.18)
- 520 Wang, X., Liu, Y., Ling, F., Liu, Y., Fang, F., 2017. Spatio-Temporal Change Detection of Ningbo Coastline
521 Using Landsat Time-Series Images during 1976–2015. *ISPRS Int. J. Geo-Inf.* 6, 68.
522 <https://doi.org/10.3390/ijgi6030068>
- 523 Ward, J.D., 1989. Comments on the geomorphology of Walvis Lagoon and environs. (No. 13/7/3/1/3).
524 Geological Survey of South West Africa/Namibia, Windhoek.
- 525 Wilkinson, M.J., Blaha, J.E., Noli, D., 1989. A new lagoon on the Namibian coast of South Africa: Sand spit
526 growth documented from STS-29 shuttle photography. *Geocarto Int.* 4, 63–66.
527 doi:10.1080/10106048909354235
- 528 Xu, H., 2006. Modification of normalised difference water index (NDWI) to enhance open water features
529 in remotely sensed imagery. *Int. J. Remote Sens.* 27, 3025–3033. doi:10.1080/014316060058917